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Dynamic Data-Driven Modeling of Uncertainties and 3D Effects of Porous Shape Memory Alloys

CRAIG DOUGLAS

UNIVERSITY OF WYOMING

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14. ABSTRACT
We implemented a multiscale model developed in year 1 for shape memory alloys (SMAs) starting from an existing solid SMA model to simulate a simple vibration isolation device. We used protocols developed in year 1 for data acquisition that allowed vibration isolation experiments to be run remotely in our dynamic data-driven application system (DDDAS) framework. DDDAS has been realized via changing the temperature of the specimen dynamically so its general hysteresis properties dynamically changes. The implementation uses PetSC and is inherently parallel on high performance computing clusters. We simulated transporting payloads into space or in high speed, highly maneuverable aircraft. One of our team members (Derrick Cerwinsky) at Wyoming received a Ph.D. and worked on the project since shortly before completing his degree and continued as a post-doc. He was been essential to the code development in year 2.

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1. Introduction

We describe results from a research project to develop a dynamic data driven application system (DDDAS) for (porous) Shape Memory Alloys (SMAs) using multiscale methods and finite element methods. A virtual shaker device is described that we used for experimentation in order to determine how many sensors were appropriate, the sampling rate, and how the sensors influenced the models.

The rest of the final report is ordered as follows. In Section 2 we describe SMAs and a mathematical model for Joule heated SMAs. In Section 3 we describe the virtual shaker device and the DDDAS. In Section 4 we discuss personnel and project management. In Appendix A, we list honors, papers, dissertations, and talks.

2. Shape Memory Alloys

In this section we describe basic properties of SMAs (Sec. 2.1) and a mathematical model for Joule heated SMAs (Sec. 2.2).

2.1. Properties of SMAs

Shape memory alloys (SMAs) and porous shape memory alloys (pSMAs) are alloys that remember shapes that can be recovered by controlling the temperature and stress. The difference between a SMA and a pSMA is that SMAs are solid and pSMAs are porous. Both are made from alloys that can shift their crystal structure under repeatable conditions. They are usually Joule heated using an electrical source. Ferromagnetic SMAs (FSMAs) are another class that change shape based on magnetism, which is faster than using heat alone.

Shape Memory Alloys are capable of changing their crystallographic structure due to changes of stress and/or temperature. These changes, referred to as Martensitic phase transformations, are associated with a transformation from a high symmetry austenitic phase to a low symmetry martensitic phase and vice versa [27]. What makes SMA materials remarkably different from ordinary metals is the shape memory effect and the pseudoelasticity effect that are associated with the specific way the phase transition occurs [11]. The shape memory effect allows material that has been deformed while in the Martensitic phase to recover its shape upon heating. The mechanism behind this behavior is the ability of SMAs to allow detwinning of the self-accommodated martensitic variants. The pseudoelasticity in SMAs is their ability to support large inelastic strains recoverable upon unloading due to the reverse phase transformation from Martensite into Austenite. The primary way in which such strains are introduced in the material is the stress induced phase transformation from Austenite into Martensite. See Fig. 1.

Most metals do not show a shape memory effect even if they can have different crystal structures. SMAs can revert to their original shape after heating since their crystal transformation is fully reversible. In standard crystal transformations the atoms in the structure travel through the metal using a diffusion process. This changes the composition locally while the metal as a unit is composed of the same atoms. A reversible transformation does not involve this diffusion of atoms. Instead all the atoms shift simultaneously to form a new structure. A geometric motivation is a parallelogram can be made out of a square by pushing on two opposing sides. At different temperatures, different structures are preferred.

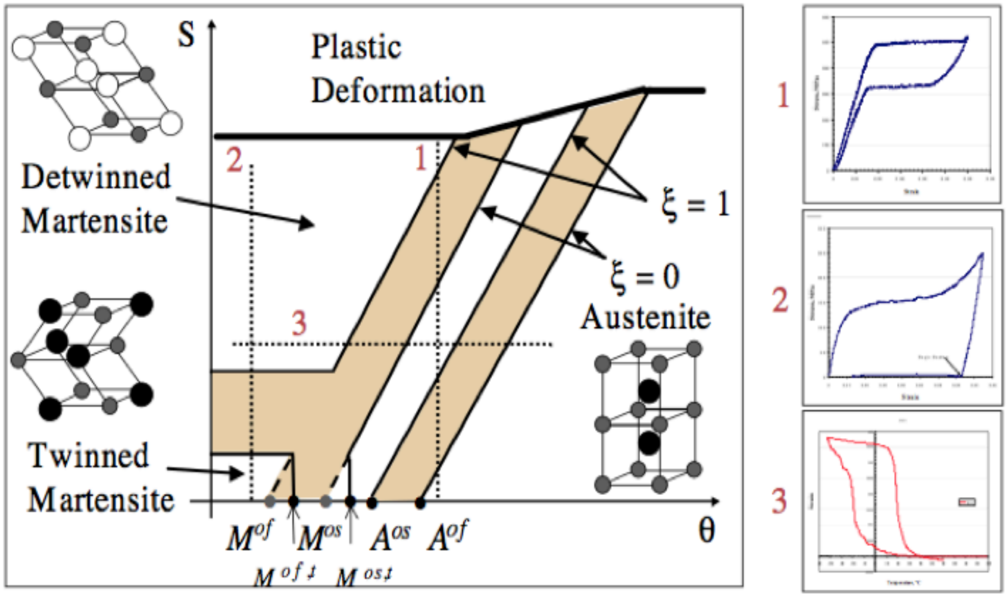

Fig. 1. Stress temperature phase diagram of an SMA

When the structure is cooled through the transition temperature the Martensitic structure forms from the Austenitic phase.

SMAs have been known since 1932 when Ölander discovered the pseudoelastic behavior when heating a Au-Cd alloy [21]. The transformation under cooling is pseudoplastic behaviour. The formation and disappearance of a Martensitic phase by decreasing and increasing the temperature of a Cu-Zn alloy was observed in 1938. The basic phenomenon of the memory effect governed by the thermoelastic behavior of the Martensite phase was reported in the late 1940's and early 1950's. The first commercially successful material, nickel-titanium alloys or Nitinol, was developed in the 1960's at the Naval Ordinance Research Laboratory and first used in 1970 in the F-14 Tomcat fighter plane.

SMAS are cast using vacuum arc melting or induction melting, which are specialist techniques used to minimize impurities in the alloy and keep the metals well mixed. The resulting ingot is typically hot rolled into longer sections and then diced. Training the alloys is subjective to what properties are desired and shapes that must be remembered. Training requires heating the alloy so that the dislocations reorder into stable positions while cool enough that the alloy does not recrystallize. SMAs are typically heated for about 30 minutes to between 400 °C and 500 °C. SMAs are shaped while hot and then cooled rapidly by quenching in water or air cooled.

In some respects, SMAs are a successor to tempered materials, e.g., steel. Since approximately 1200 BCE civilizations in Europe, Asia, and Africa have known how to make tempered steel. Pickaxes and swords are common early examples. In recent centuries, well known Dark and Middle Ages corporations (e.g., Wilkerson or Krupp Industries) have adapted to the loss of the sword business by transferring their techniques to common consumer products like razor blades and general steel products for construction.

Changing shapes is not instantaneous nor is the response time symmetrical shifting back and forth between different shapes. One of the desired shapes may take seconds to configure using Joule heat. To get back to the default shape usually takes longer since cooling is required. In fact, five to ten times longer is common. Porous SMAs using an appropriately cold liquid is one of the approaches to reduce the response time to restore the default shape.

Another approach ("lagged") to reducing the response time is to encoat the SMA in a conductive paste within a compliant shell. The heating process can be enhanced and one way in the shape change can be done faster than with just heating the SMA. The cooling time is still an issue.
SMAs have a limited life span due to naturally occurring fatigue in the alloy. Micro scale crystal breaks occur over time reducing the effectiveness of a SMA device. Heating and cooling also causes breaks. Being able to measure that a SMA device is no longer reaching exactly its expected shapes and by how much will allow for better monitoring when a SMA device needs to be replaced.

SMAs have had important impacts on materials used in the medical and aerospace industries [17], [6]. Release mechanisms (bolts that expand and contract) are used on airplane wings as well as recent convertible laptops/tablets (including a number of Windows 8 combinations). In space, SMAs are used in deploying solar panels, space station component joining, vehicular docking, and numerous Mars rover components. On airplanes or drones, jet engine intakes and exhausts, helicopter blade vibration control, and smart wings that will no longer have flaps, but will change shape dynamically. Besides aerospace applications, SMAs have given rise to their usage in a wide array of applications ranging from orthodontic wires [25] to actuators in robotic systems, self-expanding microstructures [19] and passive vibration isolation devices [28], [26], [18] for aerospace applications. A review paper [1] cited many studies on SMA devices used in industries that include mechanical, electronic, automotive, and aerospace.

SMAs can be incorporated in vibration isolation devices since (a) they can sustain large recoverable in elastic strains and dissipate high levels of energy, and (b) can actively tune and damp resonance frequencies. The porous SMA variety (a) has similar macroscopic hysteretic response as their dense counterparts, (b) offers significant weight advantages for aerospace applications, and (c) flow of a viscous phase in the pore space can be used for temperature control and additional tuning of vibration isolation characteristics.

2.2. A Mathematical Model of Joule Heated SMAs

The analysis of the existing models and their comparison to the experimental results has shown that current SMA constitutive models that take into account the development of stress-induced Martensite have reached a high level of sophistication. However, such models generally lack the ability to handle other loading paths involving detwinning and reorientation of Martensite in conjunction with the pseudoelastic response. Therefore, there is need for a 3D constitutive model that can accurately capture not only the material response during pseudoelastic and SME loading paths, but also loading paths that involve co-existence of all the three material phases: Austenite, twinned (self-accommodated) Martensite, and detwinned Martensite. Such a model was implemented numerically and tested on a comprehensive set of model problems. We performed numerical simulations of problems of varying engineering difficulty, such as the actuation of SMA micro-grips [16], the cooling/heating cycles in the manufacturing and deployment of biomedical devices [15], temperature actuated flow regulating devices [22], and fuel powered SMA actuators [14], just to name a few examples.

We utilized a 3-D constitutive model for polycrystalline Shape Memory Alloys [24]. The model is based on a modified phase transformation diagram that is able to distinguish detwinning from phase transformation behavior. The model takes into account both direct conversion of Austenite into detwinned Martensite as well as the detwinning of self accommodated Martensite (see Fig. 2). It is suitable for performing numerical simulations on SMA materials undergoing complex thermomechanical loading paths in stress-temperature space. The model is based on thermodynamic potentials and utilizes three internal variables to predict the phase transformation and detwinning of Martensite in polycrystalline SMAs. The model was tested extensively on complicated geometries. It handled complicated thermomechanical loading paths and complex geometries robustly enough so that it could be utilized in an iterative upscaling framework for porous SMAs.

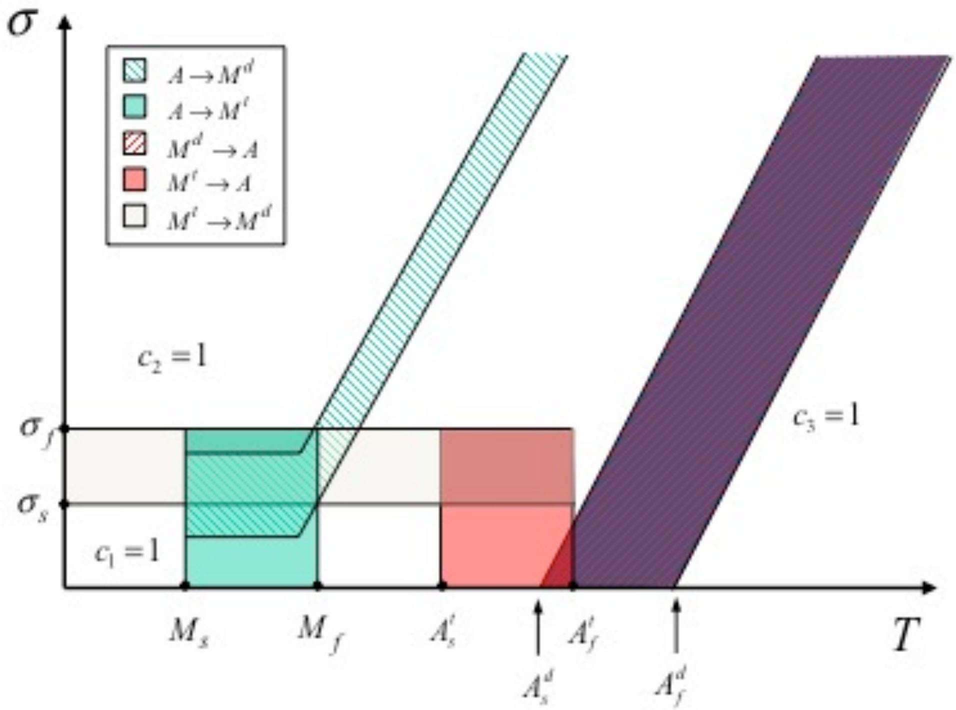

Fig. 2. SMA Phase diagram showing the different transformation regions in stress-temperature space. The diagram is extended in comparisons to previous works in order to achieve a consistent and robust model

The mass fractions of the three phases are introduced:

c_1: self-accommodated Martensite
c_2: detwinned Martensite
c_3: Austenite,

where $c_1+c_2+c_3=1$, $0\leq i\leq 1$, $i=1,2,3$. The transitions between the different species are accounted by three independent internal variables ξ_1, ξ_2, and ξ_3 that satisfy $c_1=c_{10}+\xi_1-\xi_3$, $c_2=c_{20}+\xi_2+\xi_3$, and $c_3=c_{30}-\xi_1-\xi_2$ (see Fig. 3).

We used a general form of the Gibbs free energy for a polycrystalline SMA that at any instance contained any of three species, σ is the Cauchy stress and T is temperature:

$$G = c_1 G^{(1)}(\sigma,T) + c_2 G^{(2)}(\sigma,T) + c_3 G^{(3)}(\sigma,T) + G^{MIX}(\sigma,T,c_1,c_2,\mu^{in}),$$

where the $G^{(i)}$, $i=1,2,3$ are given by

$$G^{(1)}(\sigma,T) = G^{(2)}(\sigma,T) = -\frac{1}{2\rho}\sigma : S^M : \sigma(1-\frac{1}{\rho}) : \left[\alpha^M (T-T_0) + \varepsilon^{in}\right] + c\left[T - T_0 - T\ln(T/T_0)\right] - s_0^M (T-T_0) + u_0^M$$

and

$$G^{(3)}(\sigma,T) = -\frac{1}{2\rho}\sigma : S^A : \sigma(1-\frac{1}{\rho}) : \left[\alpha^A (T-T_0) + \varepsilon^{in}\right] + c\left[T - T_0 - T\ln(T/T_0)\right] - s_0^A (T-T_0) + u_0^A$$

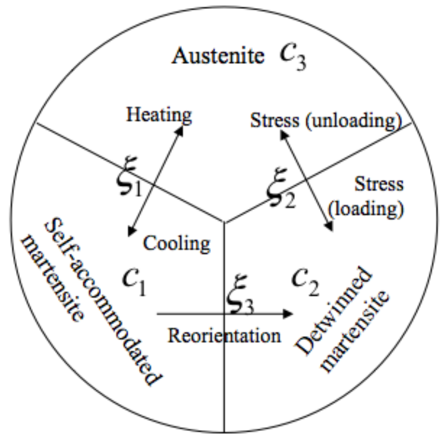

Fig 3. Internal variables for a dense SMA model

Given a set of hardening parameters b^*_{**}, the energy mixing term is given by

$$G^{MIX}(c_1, c_2) = \frac{1}{2} b_1(\dot{\varepsilon}_1)c_1^2 + \frac{1}{2} b_1(\dot{\varepsilon}_2)c_2^2 + b_{12}c_1c_2 + \mathrm{sgn}(\dot{\varepsilon}_1)\mu_1 c_1 + \mathrm{sgn}(\dot{\varepsilon}_2)\mu_2 c_2 \text{ , where}$$

$$\beta_i = \beta_i^A \text{ for } \dot{\varepsilon}_i > 0 \text{ and } \beta_i^M \text{ for } \dot{\varepsilon}_i < 0,\ i = 1,2.$$

The total inelastic strain ε^{in} was assumed to be generated only by the phase transformation and the detwinning of Martensite and was decomposed additively:

$$\varepsilon^{in} = \varepsilon^d + \varepsilon^t, \quad \dot{\varepsilon}^d = \Lambda^d \dot{\xi}_3, \quad \dot{\varepsilon}^t = \Lambda^t \dot{\xi}_2, \quad \Lambda^d = \sqrt{\frac{2}{3}} H \frac{dev(\sigma)}{\|dev(\sigma)\|} \text{ when } \dot{\xi}_3 > 0,$$

$$\Lambda^t = \sqrt{\frac{2}{3}} H \frac{dev(\sigma)}{\|dev(\sigma)\|} \text{ when } \dot{\xi}_2 > 0 \quad \text{and} \quad \Lambda^t = \sqrt{\frac{2}{3}} H \frac{dev(\varepsilon^t)}{\|dev(\varepsilon^t)\|} \text{ when } \dot{\xi}_2 < 0.$$

Here, the tensors Λ^t and Λ^d specify the flow rate for the phase transformation ($A \leftrightarrow M^d$) and the detwinning of the Martensite ($M^t \to M^d$), respectively. The second law of thermodynamics then took the form

$$T\dot{\eta} = -\left(\varepsilon - \varepsilon^{in} + \rho\frac{\partial G}{\partial \sigma}\right) : \dot{\sigma} - \rho\left(s + \rho\frac{\partial G}{\partial T}\right) : \dot{T} - \rho\frac{\partial G}{\partial \xi_1}\dot{\xi}_1 + \left(\sigma : \Lambda^t - \rho\frac{\partial G}{\partial \xi_2}\right)\xi_2$$
$$+\left(\sigma : \Lambda^t - \rho\frac{\partial G}{\partial \xi_3}\right)\xi_3 \geq 0.$$

3. Multiscale Modeling and Iterative Homogenization

Over the past few years we developed a multiscale framework for Fluid-Structure Interaction (FSI) problems that is directly relevant to our research [23]. We considered deformable porous media. Stokes flow was assumed at the pore scale and an elastic model for the pore-level deformations. Because of the complexity of the interaction at the pore level, an iterative macroscopic model was used. The macroscopic model consisted of a nonlinear Darcy equation and upscaled elasticity equations. Both constitutive relations were modeled via an iterative procedure. In each iteration, constitutive equations were derived based on macroscopic variables and local cell problems. Numerical results for the case of linear elastic solid skeleton demonstrated the well-posedness and convergence of the method. Results showed that due to changes in

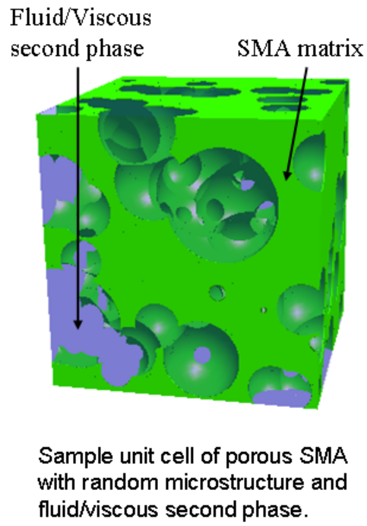

Fig. 4. A schematic of a porous SMA (green) with a fluid second phase (transparent)

the pore structure, we could substantially increase the permeability of the media. Our numerical studies showed a good agreement between the reference solution and the solution obtained from the proposed upscaled model. We also did analysis under some restrictive assumptions. The main theoretical result was a comparison between the reference fine-scale solution and the downscaled one obtained by iterative upscaling in one macro iteration. In particular, the error at iteration n was estimated, given that the error at iteration $n-1$ was small. Because of the loss of periodicity, partition of unity techniques were employed to construct the correctors for Stokes equations in locally periodic media, which were then utilized in the analysis.

We utilized existing knowledge of constitutive modeling of polycrystalline SMA in order to build a multiscale model based on iterative homogenization, which spanned two length-scales: at the fine scale the SMA formed a porous space filled by a fluid, and at the macroscale where the porous SMA skeleton and the fluid were treated as a poroelastic material (Fig. 4). The homogenization was done by iterative upscaling. This was a novel contribution to the field of SMA constitutive modeling, in terms of predicting the macroscopic response of a fluid-SMA mixture.

We developed novel multiscale computational models for our applications following the approach in [23]. Our primary tools included ideas from homogenization theory based on iterative homogenization [13], [10]. The key idea was to build fine-scale information directly into a coarse scale computational grid, thus bypassing the explicit homogenization step. This approach allowed treatment of problems with highly nonlinear coefficients and/or interface conditions by incorporating the correct fine-scale physics into the coarse level numerically. The main challenge was to adapt those tools to the highly complex and nonlinear nature of the fine scale. When bridging it we had to do uncertainty quantification [9] in ways that ensured that the coarser model retained its predictive capabilities.

The implementation issues associated with numerical upscaling methods were also formidable. They required multiple local solves of a system of nonlinear differential equation in a Representative Element of Volume (REV). This was needed for each nonlinear coarse scale iteration at each coarse grid point. In that step we used the model developed by [24], which was implemented in a robust manner in a displacement based FEM. Moreover, the homogenization step involved random geometries (e.g., the porous skeleton, various material parameters such as maximum transformation strain, etc.). Consequently, iterative homogenization schemes in such stochastic geometries were computationally very expensive [9]. The problem was compounded by the need for nonlinear iterations [7], [8]. On the other hand, homogenization theory allowed us to isolate each local problem [4], leading to a very high degree of parallelism. Hence, numerical upscaling schemes were ideally suited to extreme scale computing

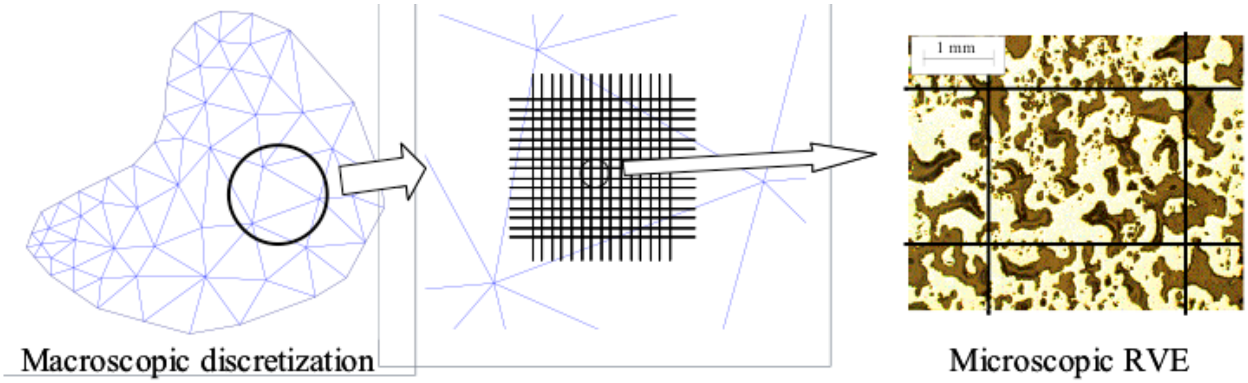

Fig. 5. Multiple scales

environments. Such computational resources, either in the form of a massively parallel distributed computer or a cloud architecture, were, in principle, sufficient to treat the model for either application by iterative homogenization. However, we really needed entirely new programming concepts as part of this work. These were mandated by the high degree of parallel flexibility required, including the preprocessing of the data at very different scales, the local computational runs themselves, and the post-processing steps. Together with proper uncertainty characterization methods, e.g., using multilevel Monte Carlo [9], iterative upscaling on emerging computing architectures has the potential to bridge all the length-scales involved in a robust way and assess the uncertainties in the predictions.

The actual methodology appeared straightforward:

- Define a multiscale mapping linking the coarse fields (displacement, stress, internal variables) to the fine scale quantities (e.g., homogenization motivated correctors).
- Initialize coarse level fields.
- Each coarse-scale integration point is mapped to the fine scale (via a local solution to a PDE).
- Once fine scale quantities are computed, appropriate averages are taken and transferred back to the coarse scale.
- Conservation of linear momentum is solved with those averages producing a new iterate for the coarse fields.

An example of the methodology is in Fig. 5.

4. DDDAS

We concentrated on a specific, relative simple shaker device: a vibrating system consisting of a pseudoelastic NiTi SMA beam in a cantilevered-pinned configuration. This is similar to a real shaker device at Texas A&M University that we received limited data from. A mass is clamped in the center of the beam. The entire system received periodic vibrations over a range of frequencies in order to determine its isolation and damping capabilities (see Fig. 6) that we fed into a multiscale finite element procedure MsFEM. Our virtual device was a simpler system compared to one with porous SMA components because the SMA model could be applied directly. We eliminated the homogenization step of the porous material and reduced the uncertainties in the analysis and design of the overall system.

In the virtual shaker environment we could modify the behavior of the sensors in ways that cannot be done on an existing, *very* expensive shaker table. The existing table produced data every 0.1 seconds per sensor. This was not necessarily optimal and our DDDAS could tell each of the virtual sensors to produce data faster, slower, or temporarily stop. This capability allowed us to better design future shaker tables or devices for taking payloads on aerospace vehicles.

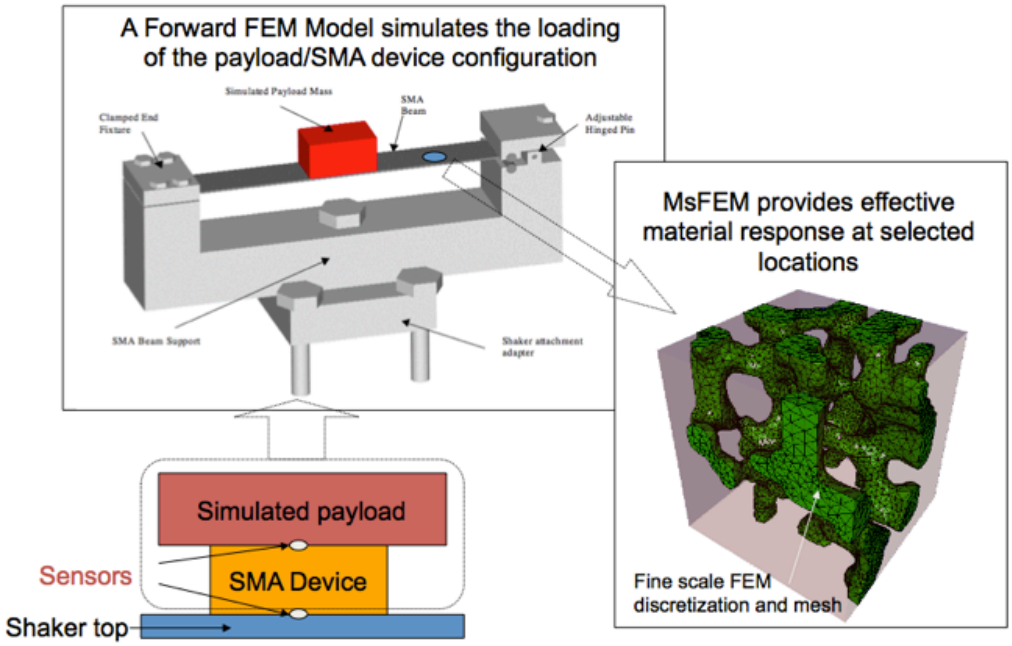

Fig. 6. Virtual shaker configuration and 3D multiscale porous SMA discretization for MsFEM code [2]

The virtual environment allowed us to vary parameters in order to study chaos, which can occur, unfortunately. Chaos is not a phenomena that is acceptable nor desired in vibration isolation devices. A careful study was required in order to guarantee that chaos was not present in such a device.

The DDDAS was realized primarily by changing the temperature of the specimen dynamically to modify its general hysteresis properties, either the Joule heating and/or the fluid flow rate in a porous SMA. Modifying the fluid pressure also let us change the effective mechanical response.

We were able to respond to long term fatigue changes in dense SMA through model parameters. We could calibrate and improve microscale (dense) SMA model parameters based on dynamic data, e.g., the maximum transformation strain, transformation temperatures, etc. The DDDAS components interacted with the forward simulations of the shaker device setup to manage data streams and feedback control.

The feedback control loop in the DDDAS is given in Fig. 7. MsFEM interacted with the DDDAS communication subsystem, which in turn communicated with the sensors. Based on the vibrations measured, we modified the SMA based on a prediction-correction process that was trained in advance, but operated dynamically.

Fig. 8 provides an example of a payload on the shaker table environment that goes from a steady state to a state caused by oscillation. The plot shows the (x,y) location of a single sensor at the center of the payload. Initially the sensor is at (0,0) and immediately begins moving. The sensors detected the movement and changed the configuration of the SMA to stabilize the particle. The DDDAS model was used to predict the future state of the particle and the SMA was modified accordingly. Due to the chaotic nature of the vibrations the model predictions were an educated guess. Hence, sensors were required to capture the actual state of the particle and the model was updated accordingly.

Once the SMA's shape changed the particle stabilized and remained in a steady state until random oscillations once again required a modification in the SMA.

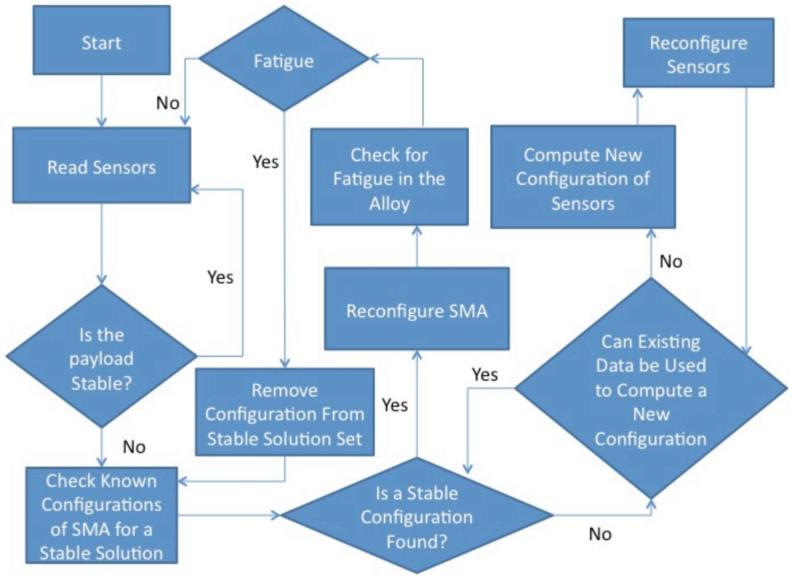

Fig. 7. DDDAS feedback control loop

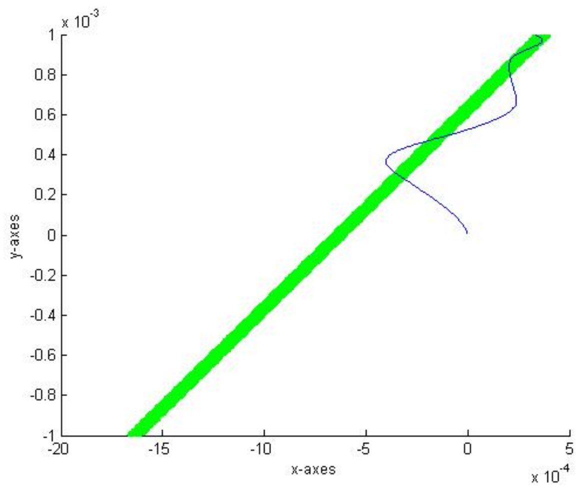

Fig. 8: Orbits of simple shaker table example

The oscillation used for this simulation were relatively simple oscillation that led to two stable nodes, as seen in Fig. 8. Three dimensional oscillations have a much more complex orbit structure and can even exhibit chaos. In these cases, the need for DDDAS feedback cannot be understated.

4. Personnel and Project Management

Craig Douglas (PI, University of Wyoming) led the project and oversaw programming issues and details of the DDDAS. Yalchin Efendiev (Co-PI, Texas A&M University) oversaw the multiscale issues and details. Peter Popov (Co-PI, Texas A&M University) provided expertise on SMAs and a code that we started from for developing the virtual shaker. Derrick Cerwinsky (University of Wyoming) was hired first as a graduate research assistant (receiving a Ph.D. [2] in December 2012) and then as a postdoctoral scientist to work on the project.

Originally, Dr. Popov was supposed to spend several months in each of 2012 and 2013 working on the project. Due to personal issues, he was not able to be at Texas A&M in 2013 and was replaced by Dr. Cerwinsky.

The grant was extended by one month in order for the PI to attend a program PI workshop in Arlington, VA from 30-09-2013 to 02-10-2013.

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Appendix A. Honors, Papers, Dissertations, and Talks

A.1. Honors

Donald Brown, L.F. Guseman Prize in Mathematics, 2012.
Donald Brown, 2013 InterPore-Fraunhofer Award for Young Researchers, awarded by the International Society for Porous Media.

A.2. Papers

C. C. Douglas, Y. Efendiev, P. Popov, and V. Calo, *An introduction to a porous shape memory alloy dynamic data driven application system*, Procedia Computer Science, 9 (2012), pp. 1081-1089.
C. C. Douglas and M. V. Kritz, *A glimpse on environmental probes*, in Proceedings of DCABES 2012, Guilin, China, 2012, Q. Guo and C. C. Douglas (eds.), IEEE Computer Society CPS, Los Alamitos, CA, 2012, pp. 473-476.
C. C. Douglas, V. M. Calo, D. C. Cerwinsky, Y. R. Efendiev, *Using shape memory alloys: a dynamic data driven approach*, Procedia Computer Science, 18 (2013), pp. 1844-1850.
Y. Efendiev, J. Galvis, M. Presho, G. Li. *Generalized multiscale finite element methods. nonlinear elliptic equations*, Communication in Computational Physics, 15 (2014), pp. 733-755.D. Brown, Y. Efendiev, P. Popov, *Effective equations for fluid-structure interaction with Applications to aoroelasticity*, to appear in Applicable Analysis, 2014. DOI:10.1080/00036811.2013.839780.
Y. Efendiev, J. Galvis, M. Presho. J. Zhou, *A multiscale enrichment procedure for nonlinear monotone operators*, to appear in Mathematical Modeling and Numerical Analysis. DOI: http://dx.doi.org/10.1051/m2an/2013116.

A.3. Ph.D. Dissertations

Donald Brown, Ph.D., Texas A&M University (College Station, TX), Applied Mathematics, June, 2012.
Derrick Cerwinsky, Ph.D., University of Wyoming (Laramie, WY), Mathematics, December, 2012, *The*

Theory and Practice of Algebraic Multigrid Methods.
Michael Sollami, Ph.D., University of Wyoming (Laramie, WY), Mathematics, December, 2013, *Computational Graph Theory*.

A.4. Talks

C. C. Douglas, IAMCS Spring Symposium 2012, King Abdullah University of Science & Technology, Thuwal, Saudi Arabia, Petascale hydrologic modeling: needs and challenges, May, 2012. Invited.
C. C. Douglas, International Conference on Computational Sciences 2012, DDDAS 2012 Workshop, Omaha, U.S., An introduction to a porous shape memory alloy dynamic data driven application system, June, 2012.
C. C. Douglas, Chinese Academy of Sciences, Beijing, P.R. China, An introduction to a porous shape memory alloy dynamic data driven application system, January, 2013. Invited.
C. C. Douglas, King Abdullah University of Science & Technology, Thuwal, Saudi Arabia, Dynamic data driven apps, February, 2013.
C. C. Douglas, Hong Kong University of Science and Technology, Hong Kong, An introduction to a porous shape memory alloy dynamic data driven application system, March, 2013.
C. C. Douglas, International MultiConference of Engineers and Computer Scientists 2013, Hong Kong, Very long term simulations using dynamic data driven apps, March, 2013. Invited keynote.
C. C. Douglas, Data-Intensive Scientific Discovery 2013, Shanghai, P.R. China, Big Data and Its Applications, August, 2013. Invited keynote.
12th Conference on Fluid Flow through Porous Media, Chinese University of Petroleum, Qingdao, P.R. China, A fast method for predicting moisture movement through porous media, August, 2013. Invited.
C. C. Douglas, University of Wyoming, Big data and dynamic apps in a nutshell, October, 2013.
Y. Efendiev, 8th East Asia SIAM Conference, National Taiwan University, Taipei, Taiwan, June, 2012. Invited keynote.
Y. Efendiev, ICES, UT Austin, Generalized multiscale finite element methods, Multiscale Modeling Workshop, April, 2013. Invited.
Y. Efendiev, 5th International Conference on Porous Media and Annual Meeting, Prague, Czech Republic, Generalized multiscale finite element methods, May, 2013.
Y. Efendiev, Generalized multiscale finite element methods for processes in heterogeneous porous media". Porous Media Processes and Mathematics Annual Meeting, Edinburgh, UK, Jan., 2014. Invited talk.
Y. Efendiev, International Congress of Mathematicians, Seoul, South Korea, Multiscale model reduction for flows in heterogeneous media, August, 2014. Invited.